International Journal of Accounting and Financial Management Research (IJAFMR)
ISSN(P): 2249-6882; ISSN(E): 2249-7994
Vol. 9, Issue 2, Dec 2019, 1-14

THE PREDICTION OF FINANCIAL PERFORMANCE OF BANKS USING ARTIFICIAL NEURAL NETWORK

V. K. VISWANATHA RAJU[1] & V. V. S. KESAVA RAO[2]

[1]Student, Department of Mechanical Engineering, College of Engineering(A), Andhra University, Visakhapatnam, India

[2]Professor, Department of Mechanical Engineering, College of Engineering(A), Andhra University, India

ABSTRACT

In this paper an effort is made to predict the financial performance of public sector banks in India based on their financial soundness and financial efficiency. Clustering analysis is applied to group the banks in three different categories as clustering groups as LL, MM and HH. ANN-MLP is applied to verify the results of clustering analysis and also to determine the importance given by ANN to CAMEL ratios.

KEYWORDS: CAMEL Ratios, Clustering Analysis & MLP-ANN

Received: May 24, 2019; **Accepted:** Jun 13, 2019; **Published:** Jun 29, 2019; **Paper Id.:** IJAFMRDEC20191

Original Article

INTRODUCTION

In this paper an effort is made to predict the financial performance of banks based on financial soundness and financial efficiency using artificial neural network analysis. It is generally recognized that company financial statements provide information on a company's performance, stability and indication of future commercial and financial prospects. Analysis and interpretation of financial statements using various ratios and studies of trends do provide a shareholder, creditor, banker or potential investor valuable information about a company's financial status, its solvency position, and its borrowing power and whether the company is a suitable investment for shareholders.

Having the ability to predict company failures is of the utmost importance. Managers trained in using selected and proven financial ratios as analytical tools and being aware of financial soundness prediction models can take corrective and preventive measures to prevent failure in their own companies. Individuals as well as institutional investors and fund managers who manage large investment portfolios can improve their performances if they can distinguish the weak companies from the healthy ones. Such knowledge and skills in ratio analysis and financial prediction models can be very useful to the statutory auditors who are required by law to determine a company's ability to continue its existence as a going concern.

Generally, financial distress precedes business failure and demise. Therefore, assessing the financial soundness of a business on a periodic basis, gives the analyst, valuable insights about the performance and status of the business and companies under review. An early warning system model that can anticipate distress and can give indications of financial troubles ahead would doubtless be useful in minimizing or outright avoidance of exposure to possible substantial losses for their own companies and shareholders or their clients.

In this study, financial performance prediction model using neural network analysis the CAMEL ratios and earnings per share ratio to achieve a much higher prediction accuracy rates for financial performance condition. Multi Layer Perceptron of artificial neural network approach is implemented using SPSS 17.0.

One interesting area for the use of neural networks is in event prediction. This study develops a neural network model for prediction of the financial soundness of steel manufacturing organizations and tests it using financial data from these organizations. A comparison of the predictive abilities of both the neural network and the discriminant analysis method is presented. The results show that neural networks might also be applicable to predict financial soundness of business organizations.

Assessment of the financial situation of the enterprise through financial analysis is a complex expression of levels of all business activities that the company is presented to the market. Its analysis is the starting point for analysis of the economic performance of the company, its efficiency, capacity utilization, profitability, solvency and liquidity, but also for stocks, receivables management and debt. Through financial soundness analysis can identify the strengths and weaknesses in the enterprise, diagnose its financial health and to identify the causes that determined the financial situation of the company. Assessment of the financial soundness of the companies and industries where they operate is in today's turbulent time’s matter of great importance.

Financial performance prediction based on financial soundness and financial efficiency has been an important and widely studied topic in accounting and finance because it’s significant impact on management, employees, stockholders, and the nation. Accuracy is one of crucial performance due to its significant economic impact, numerous statistical techniques have been used for improving the performance of financial soundness prediction models, such as univariate analysis, discriminate analysis, logistic models. Studies of financial soundness prediction continuously developed by academician and companies by using various models are found in literature. The artificial neural network was one of the models to predict the financial performance of business organizations.

The aim of the research presented in the thesis is to evaluate the financial situation in the banking sector.

ARTIFICIAL NEURAL NETWORKS

Neural networks are the preferred tool for many predictive data mining applications because of their power, flexibility, and ease of use. Predictive neural networks are particularly useful in applications where the underlying process is complex, such as:

- Forecasting consumer demand to streamline production and delivery costs.
- Predicting the probability of response to direct mail marketing to determine which households on a mailing list should be sent an offer.
- Scoring an applicant to determine the risk of extending credit to the applicant.
- Detecting fraudulent transactions in an insurance claims database.

Neural networks used in predictive applications, such as the multilayer perceptron (MLP) networks, are supervised in the sense that the model-predicted results can be compared against known values of the target variables. The Neural Networks option allows fitting MLP and saving the resulting models for scoring.

Neural Network Structure

Although neural networks impose minimal demands on model structure and assumptions, it is useful to understand the general network architecture. The multilayer perceptron (MLP) network is a function of predictors (also called inputs or independent variables) that minimize the prediction error of target variables (also called outputs). Consider the bankloan.sav dataset that ships with the product, in which you want to be able to identify possible defaulters among a pool of loan applicants. An MLP network applied to this problem is a function of the measurements that minimize the error in predicting default.

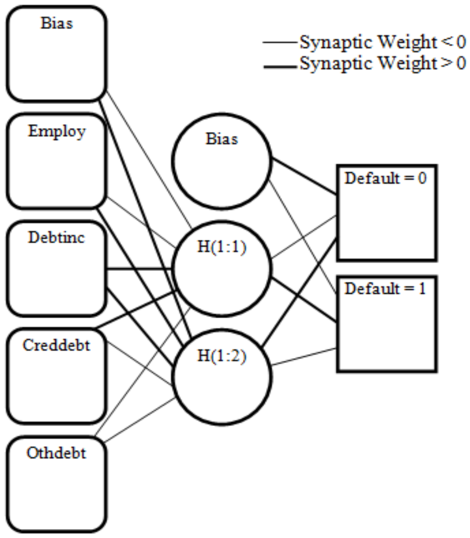

Figure 1: Feed Forward Architecture with One Hidden Layer

This structure is known as a feedforward architecture because the connections in the network flow forward from the input layer to the output layer without any feedback loops. In this figure:

- The input layer contains the predictors.
- The hidden layer contains unobservable nodes, or units. The value of each hidden unit is some function of the predictors; the exact form of the function depends in part upon the network type and in part upon user-controllable specifications.
- The output layer contains the responses. Since the history of default is a categorical variable with two categories, it is recoded as two indicator variables. Each output unit is some function of the hidden units. Again, the exact form of the function depends in part on the network type and in part on user-controllable specifications.

The MLP network allows a second hidden layer; in that case, each unit of the second hidden layer is a function of the units in the first hidden layer, and each response is a function of the units in the second hidden layer.

Multi-Layer Perception (MLP)

The commonly used architecture of neural network system used in insolvency prediction are: 1. Multilayer perception (MLP) with a “back-propagation” algorithm: the most popular ANN architecture used in insolvency prediction (Perez, 2006). This architecture deals with classification problems via a sigmoidal or ‘squashing’ activation function. The figure below represents the layout of perception neurons in an MLP neural network, in which there are two neuron

layers, one hidden and one output. Regarding the neural network that is presented in the figure, each neuron of the hidden layer is connected to each neuron in the output layer. The analyst that uses the artificial neural network algorithm must choose how many neurons to use in the hidden layer. Considering the set of input data, since with a low number of neurons in the hidden layer, the neural network is not able to generalize each class's data. However, a high number of neurons in the hidden exclusively learn training data, and does not generalize learning for data classes.

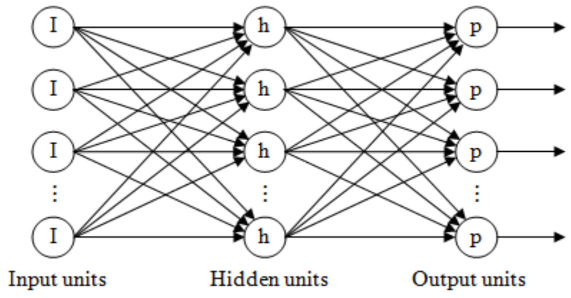

Figure 2: Multi-Layer Perception

LITERATURE SURVEY

Aslani et al. (2009) [1] investigated the performance of radial basis function network and the multi-layered perceptron network for evaluating the branch efficiency of a big Iranian bank. The comparisons on parameter settings between the MLP and RBF neural network models is made in the paper.

Qeethara Kadhim Al-Shayea, et al. (2011) [2] made a study is to predict bank insolvency before the bankruptcy using artificial neural networks, to enable all parties to take remedial action. Artificial neural networks are widely used in finance and insurance problems. Generalized Regression Neural Network (GRNN) is used to evaluate the predictor variable used to predict the insolvency. The percent correctly classified in the training sample by the feed-forward back propagation network is approximately 91 percent is obtained in the study.

Noraina Mazuin Sapuan et al. (2017) [3] applied neural networks successfully in wide range of business tasks and were able to detect complex and nonlinear relationships without requiring any specific assumptions about the distribution or characteristics of the data. In the study, the authors are able to predict the survival predictors for the Islamic banks and able to identify the directions for each predictors.

Mohamed M. Mostafa (2009) [4] investigated the efficiency of top Arab banks using two quantitative methodologies: data envelopment analysis and neural networks. The study uses a probabilistic neural network (PNN) and a traditional statistical classification method to model and classify the relative efficiency of top Arab banks. The study highlights the economic importance of encouraging increased efficiency throughout the banking industry in the Arab world.

Peter Wanke et.al. (2016) [5] presented an efficiency assessment of the Malaysian Islamic banks using two stage TOPSIS and Neural Networks Approach. The results reveal that variables related to cost structure have a prominent negative impact on efficiency levels, although some parsimony in equity lever-aging derived from Islamic finance principles may be helpful in achieving higher efficiency levels.

Elsa Shokrollahpour et.al. (2016) [6], integrated artificial neural network with DEA to calculate the relative efficiency and more reliable benchmarks of one of the Iranian commercial bank branches. The study is helpful to develop a

strategy to improve the efficiency and eliminate the cause of inefficiencies based on a 5-year time forecast of the banking authorities.

Hsiang-Hsi Liu et.al. (2013) [7] considered data envelopment analysis (DEA), three-stage DEA (3SDEA) and artificial neural network (ANN) are employed to measure the technical efficiency of 29 semi-conductor firms in Taiwan. Estimated results show that there are significant differences in efficiency scores among DEA, 3SDEA and ANN analysis. The advanced setting of the three stages mechanism of DEA does show some changes in the efficiency scores between DEA and ANN approaches.

Krzysztof Piasecki, et al. (2017) [8] investigated the use of different structure NN and DA in the process of the classification of banks' potential clients. The results of these different methods are juxtaposed and their performance compared.

Nor Mazlina Abu Bakar, et al. (2009) [9] made a study to predict bank performance using multiple linear regression and neural network. The study then evaluates the performance of the two techniques with a goal to find a powerful tool in predicting the bank performance. Data of thirteen banks for the period 2001-2006 was used in the study. The study concluded that artificial neural network is the more powerful tool in predicting bank performance.

Ayan Mukhopadhyay et.al. (2012) [10] combined Data Envelopment Analysis and Multi-Layer Perceptron (MLP) to suggest a new method for prediction of bankruptcy that not only focusses on historical financial data of firms. The proposed method thus identifies firms that have a high chance of facing bankruptcy along with those that have filed for bankruptcy.

Olanrewaju A Oludolapo et.al. (2012) [11] presented techniques based on the development of multilayer perceptron (MLP) and radial basis function (RBF) of artificial neural network (ANN) models, for calculating the energy consumption of South Africa's industrial sector between 1993 and 2000. The approach examines the energy consumption in relation to the gross domestic product. The results indicate a strong agreement between model predictions and observed values,

Mehdi Alinezhad Sarokolaei et.al. (2012 [12] made a research to forecast the performance of 10 Iranian banks using multi-linear regression method and artificial neural network and to compare these two methods. To do so, the financial data related to 10 Iranian banks during the years between 2006 and 2010 were collected from the most reliable resources.

Viju Raghupathi, et al. (2015) [13] deployed neural networks to examine the strategic association between hospitalization experience and treatment results. The healthcare data for the years 2009-2012 are downloaded from the Statewide Planning and Research Cooperative System (SPARCS) of the New York State Department of Health (NYSDOH).

Mahmoud H. Al-Osaimy (1998) [14] used neural networks for predicting Islamic bank's performance. A data sample of twenty six Islamic banks has been collected for the period 1991 1993. Seven financial ratios were constructed from the data sample. Kohonen neural network was used first to group the Islamic banks into high and low performance groups using the seven financial ratios for the performance year (1993). The results of this network have assigned twelve banks to the high performance group and fourteen banks to the low performance group.

Satish Sharma, et al. (2013) [15] presented an application of neural network and simulation modelling to analyze and predict the performance of 883 Russian Banks over the period 2000-2010. A neural network was trained over the entire dataset, and then simulation modelling was performed generating values. Next, a combination of neural network and simulation modelling techniques was validated with the help of back-testing.

Faruk Erinci, et al. (2016) [16] have been estimated future-oriented performance using 2457 input and 364 output normalized data of 28 deposit bank continuously operating during 2002-2014 in the Turkish Banking Sector. The study is helpful in the banking sector to the decision-making experts to help with these parameters and for the visualization of prediction results for the future.

METHODOLOGY

Seventeen CAMEL ratios along with earnings per share ratios of 20 public sector banks in India during five financial years Financial soundness ranking obtained by integrating AHM-GRA-DEA method and composite ranking of financial efficiency obtained through super efficiency and cross efficiency approaches of DEA are considered for grouping the banks through cluster analysis. Range of the grouping variable is considered as: 1) Low financial soundness and Low financial efficiency (LL), 2) Medium financial soundness and Medium financial efficiency (MM), 3) High financial soundness and High financial efficiency (MM). The grouping is made through cluster analysis using the financial soundness ranks and financial efficiency ranks obtained in chapter three and four respectively

RESULTS AND DISCUSSIONS

The aim of this study was to predict overall financial performance through MLP neural networks of the 20 Indian public sector bank organizations. MLP of Neural networks is implemented to the case study and the following outputs of the analysis are discussed in the following sections.

Table 1: Financial Soundness Ranking

Bank	Financial Year				
	1st Year	2nd Year	3rd Year	4th Year	5th Year
Bank1	9	6	18	19	18
Bank2	3	4	7	15	9
Bank3	2	2	5	2	2
Bank4	13	13	12	4	8
Bank5	20	10	3	11	15
Bank6	6	11	15	9	11
Bank7	12	20	19	20	19
Bank8	4	3	4	7	12
Bank9	1	5	1	1	3
Bank10	5	1	9	8	7
Bank11	17	14	17	18	20
Bank12	8	17	14	12	14
Bank13	7	9	8	14	16
Bank14	10	12	6	5	1
Bank15	14	7	10	10	5
Bank16	11	16	11	16	6
Bank17	16	8	2	3	4
Bank18	19	18	16	6	17
Bank19	15	15	13	13	10
Bank20	18	19	20	17	13

Table 2: Financial Efficiency (Composite) Ranking

Bank	Financial Year				
	1st Year	2nd Year	3rd Year	4th Year	5th Year
Bank1	13	10	14	15	12
Bank2	15	14	15	18	13
Bank3	4	2	1	5	8
Bank4	8	9	8	10	5
Bank5	20	19	13	20	17
Bank6	7	7	9	7	1
Bank7	10	19	17	6	17
Bank8	5	5	5	7	16
Bank9	18	15	16	19	14
Bank10	12	10	12	13	10
Bank11	16	15	18	17	20
Bank12	9	8	10	9	3
Bank13	2	2	3	14	10
Bank14	5	6	4	4	2
Bank15	1	1	2	1	7
Bank16	3	4	7	2	3
Bank17	14	13	6	11	9
Bank18	18	18	19	15	15
Bank19	11	12	10	11	6
Bank20	17	17	19	3	19

Initially, cluster analysis is adopted to classify the banks into groups based on ranks of financial soundness and financial efficiency using K-means clustering through Mini-Tab.

Results of Clustering Analysis

The results of clustering analysis are shown in Table 3.

Table 3: Clustering of Banks

S. No	Bank	Financial Years									
		1st Year		2nd Year		3rd Year		4th Year		5th Year	
		CLN	CLG	CLN	CLG	CLN	CLG	CLN	CLG	CLN	CLG
1	Bankl	2	MM	2	MM	1	LL	1	LL	1	LL
2	Bank2	2	MM	2	MM	2	MM	1	LL	2	MM
3	Bank3	3	HH	3	HH	3	HH	3	HH	2	MM
4	Bank4	3	HH	3	HH	3	HH	2	MM	3	HH
5	Bank5	1	LL	1	LL	2	MM	1	LL	1	LL
6	Bank6	3	HH	3	HH	1	LL	3	HH	3	HH
7	Bank7	2	MM	1	LL	1	LL	1	LL	1	LL
8	Bank8	3	HH	3	HH	3	HH	3	HH	1	LL
9	Bank9	2	MM	2	MM	2	MM	2	MM	2	MM
10	Bank10	2	MM	2	MM	2	MM	2	MM	2	MM
11	Bank11	1	LL	1	LL	1	LL	1	LL	1	LL
12	Bank12	2	MM	1	LL	1	LL	3	HH	3	HH
13	Bank13	3	HH	3	HH	3	HH	1	LL	1	LL
14	Bank14	3	HH	3	HH	3	HH	3	HH	3	HH
15	Bank15	3	HH	3	HH	3	HH	3	HH	3	HH
16	Bank16	3	HH	3	HH	3	HH	3	HH	3	HH
17	Bank17	1	LL	2	MM	3	HH	2	MM	2	MM
18	Bank18	1	LL	1	LL	1	LL	2	MM	1	LL
19	Bank19	1	LL	1	LL	1	LL	1	LL	3	HH
20	Bank20	1	LL	1	LL	1	LL	3	HH	1	LL

Note*: CLN-Cluster number; CLG-Cluster Group;

The banks in cluster number 1 are designated as LL cluster group. These banks are showing poor financial soundness and poor financial efficiency. Hence these banks can be classified as low overall performance group.

The banks in cluster number 2 are designated as MM cluster group. These banks are showing Medium financial soundness and Medium financial efficiency. Hence these banks can be classified as medium overall performance group

The banks in cluster number 3 are designated as HH cluster group. These banks are showing high financial soundness and high financial efficiency. Hence these banks can be classified as high overall performance group

MLP Network Information

- Number of inputs = 18 Financial Ratios.
- Number of output units =5(financial Soundness Groups: HH, HL, MM, LH and LL)
- Maximum number of hidden units = 50
- Training dataset = 100% of the sample
- Type of training = Batch training
- Optimizing Algorithm = scaled congregated method
- Training options, Initial λ = 0.0000005

Case Processing Summary

Table 4 gives information about the datasets used to build the ANN model. From the table it is observed that the training dataset contains in 100% of the sample.

Table 4: Case Processing Summary

		N	Percent
Sample	Training	100	100.0%
Valid		100	100.0%
Excluded		0	
Total		**100**	

Network Information

The Table 5 shows network information. The table shows the number of neurons in every layer and one independent variable (Financial performance group) denoted as cluster number (CLN). Automatic architecture selection chose 14 nodes for the hidden layer, while the output layer had 3 nodes to code the depended variable overall financial performance. For the hidden layer the activation function was the hyperbolic tangent, while for the output layer also the Softmax function is used.

Table 5: Network Information

Input layer	Factors	1	CA1
		2	CA2
		3	CA3
		4	AQ1
		5	AQ2
		6	AQ3
		7	ME1
		8	ME2
		9	ME3
		10	EQ1
		11	EQ2
		12	EQ3
		13	EQ4
		14	LI1
		15	LI2
		16	LI3
		17	EPS
		18	LI4
	Number of Units[a]		1603
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		7
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	CLN
	Number of Units		3
	Activation Function		Softmax
	Error Function		Cross-entropy
a. Excluding the bias unit			

Model Summary

The model summary is shown in Table 6.

Table 6: Model Summary

Training	Cross Entropy Error	.094
	Percent Incorrect Predictions	0.0%
	Stopping Rule Used	Training error ratio criterion (.001) achieved
	Training Time	0:00:08.94
Dependent Variable: CLN		

Table 6 provides information related to the results of training and testing sample. Cross entropy error that network minimizes error during the training phase. The cross entropy error (0.094) is obtained for training data set, meaning that the network model has not been over fitted to the training data. From the results, it is observed that, there are 100% correct predictions for training data set.

Classification Summary

Table 7 displays classification for categorical dependent variable (financial Soundness).

Table 7: Classification

Sample	Observed	Predicted			
		1.00	2.00	3.00	Percent Correct
Training	1.00	36	0	0	100.0%
	2.00	0	25	0	100.0%
	3.00	0	0	39	100.0%
	Overall Percent	36.0%	25.0%	39.0%	100.0%
Dependent Variable: CLN					

As can be seen, the MLP network correctly classified 100% banks in all the cluster groups, in the training sample.

The receiver operating characteristic curve (ROC) is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The true-positive rate is also known as sensitivity and the false-positive rate is also known as specificity. The ROC curve is shown in Figure 3.

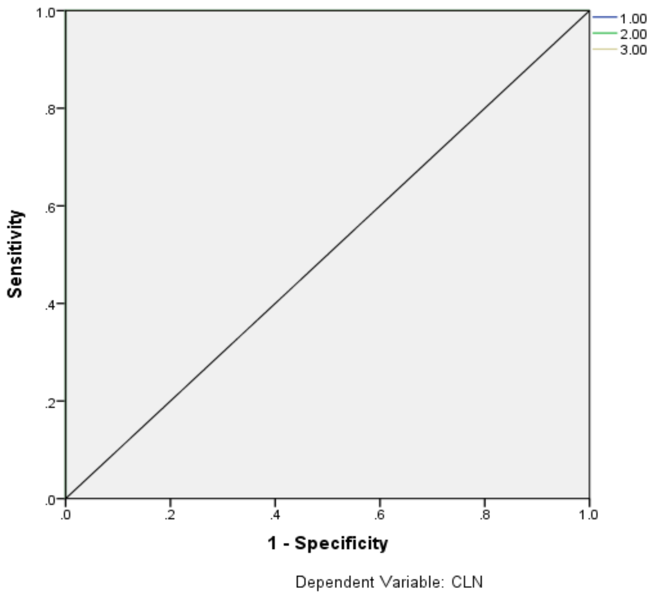

Figure 3: ROC Curve

The 45-degree line from the upper right corner of the chart to the lower left represents the scenario of randomly guessing the class. The more the curve moves away the 45-degree baseline, the more accurate is the classification. In this study, these curves are at maximum distance from the 45-degree line. Table 8 gives the area under the ROC curve.

Table 8: Area under the Curve

CLN	Area
1	1.000
2	1.000
3	1.000

The accuracy of prediction of overall financial performance measured by MLP is measured by the area under the ROC curve. An area of 1 represents a perfect test; an area of .5 represents a worthless test. A rough guide for classifying the accuracy of prediction is Excellent (0.9 to 1.0), Good (0.8 to 0.9), Fair (0.7 to 0.8), Poor (0.6 to 0.7) and Fail (0.5 to 0.6). Excellent prediction of overall financial performance is obtained through the proposed MLP is obtained in this study, since the area under ROC for all groups is equal to 1.0. Cumulative gains chart for each categorical dependent variable is shown in Figure.4.

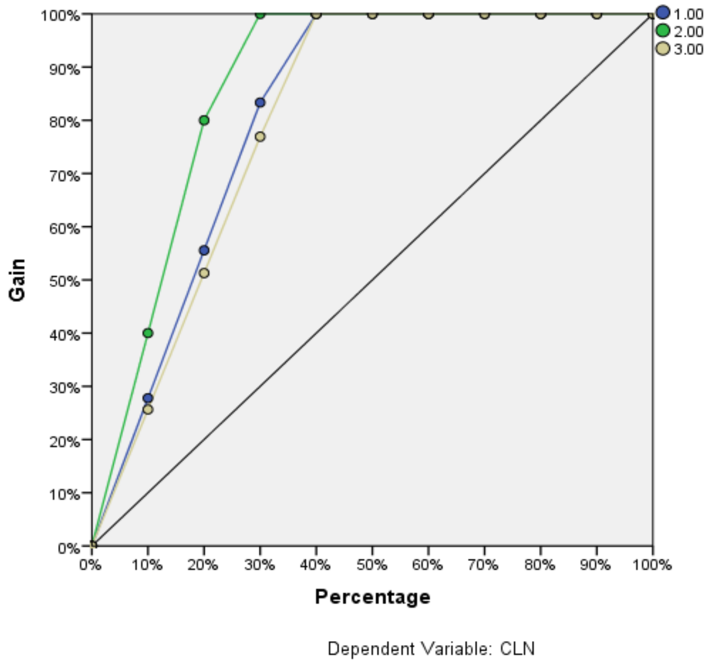

Figure 4: Cumulative Gain Chart

The chart in Figure 4 gives the cumulative gains that is the presentence of correct classifications obtained by the ANN model against the correct classifications that could result by chance (i.e. without using the model). Gain is a measure of the effectiveness of a classification model calculated as the percentage of correct predictions obtained with the model, versus the percentage of correct predictions obtained without a model (baseline). The farther above the baseline a curve lies, the greater the gain. In the study, a higher overall gain is obtained indicates better performance. Lift chart, as well as gain chart are visual aids for evaluating performance of classification models.

Importance Analysis

Table 9 gives the impact of each independent variable in the ANN model in terms of relative and normalized importance.

Table 9: Independent Variable Importance

Variable	Importance	Normalized Importance	Variable	Importance	Normalized Importance
CA1	0.0538	0.788	EQ1	0.0610	0.894
CA2	0.0568	0.832	EQ2	0.0609	0.893
CA3	0.0564	0.826	EQ3	0.0580	0.851
AQ1	0.0574	0.841	EQ4	0.0511	0.749
AQ2	0.0556	0.815	LI1	0.0503	0.738
AQ3	0.0529	0.775	LI2	0.0535	0.784
ME1	0.0516	0.755	LI3	0.0548	0.803
ME2	0.0682	1.000	LI4	0.0509	0.746
ME3	0.0523	0.767	EPS	0.0544	0.797

From the Table 9, it is apparent that the financial ratio namely: ME2 has the greatest effect on financial performance since the importance of the variable is 0.0682. LI1 has the lowest effect on the financial performance since the importance of the variable is 0.0503. In Figure. 5 the normalized importance is graphically shown i.e., histograms in the ascending order.

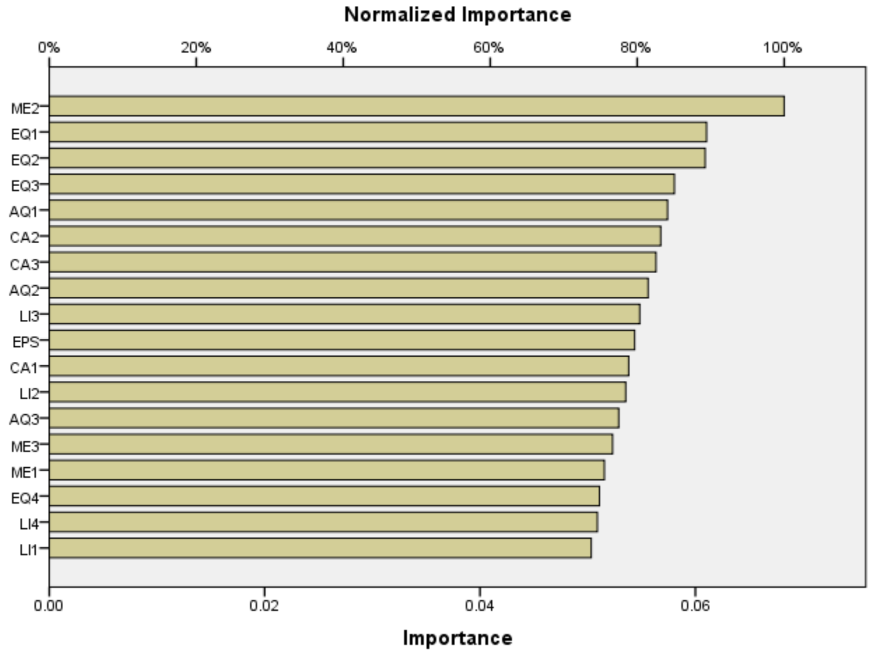

Figure 5: Normalized Importance

Artificial neural networks appear to be a powerful tool for the prediction of the financial performance of banks. Artificial neural network models are increasingly used in scoring with varying success. According to some statisticians, although these new methods are interesting and sometimes more efficient than traditional statistical techniques, they are also less robust and less well founded. Furthermore, neural networks are unable to explain the results they provide. Finally, they are as black boxes with unknown operating rules. They create their own representation in learning. In terms of interpretation of weights, neural networks seem to be more efficient.

Table 10: Overall Financial Performance Prediction

S.No	Bank	Financial Years									
		2010-11		2011-12		2012-13		2013-14		2014-15	
		CLN by CA	CLN by MLP	CLN by CA	CLN by MLP	CLN by CA	CLN by MLP	CLN by CA	CLN by MLP	CLN by CA	CLN by MLP
1	Bank1	2	2	2	2	1	1	1	1	1	1
2	Bank2	2	2	2	2	2	2	1	1	2	2
3	Bank3	3	3	3	3	3	3	3	3	2	2
4	Bank4	3	3	3	3	3	3	2	2	3	3
5	Bank5	1	1	1	1	2	2	1	1	1	1
6	Bank6	3	3	3	3	1	1	3	3	3	3
7	Bank7	2	2	1	1	1	1	1	1	1	1
8	Bank8	3	3	3	3	3	3	3	3	1	1
9	Bank9	2	2	2	2	2	2	2	2	2	2
10	Bank10	2	2	2	2	2	2	2	2	2	2
11	Bank11	1	1	1	1	1	1	1	1	1	1
12	Bank12	2	2	1	1	1	1	3	3	3	3
13	Bank13	3	3	3	3	3	3	1	1	1	1
14	Bank14	3	3	3	3	3	3	3	3	3	3
15	Bank15	3	3	3	3	3	3	3	3	3	3
16	Bank16	3	3	3	3	3	3	3	3	3	3
17	Bank17	1	1	2	2	3	3	2	2	2	2
18	Bank18	1	1	1	1	1	1	2	2	1	1
19	Bank19	1	1	1	1	1	1	1	1	3	3
20	Bank20	1	1	1	1	1	1	3	3	1	1

From Table 10 it is observed that similar grouping of banks based on overall performance is obtained by both cluster analysis and MLP of neural network analysis is obtained. But, in the MLP of neural network analysis the relative importance of financial ratios in classifying the banks into five overall financial groups is possible.

CONCLUSIONS

The aim of this paper is to predict overall financial performance of banks through artificial neural networks based on financial soundness and financial efficiency using financial ratios data collected from annual reports of twenty Indian public sector banks. The literature review indicated that neural networks outperform all other classifiers, regarding prediction accuracy. Multilayer perceptron neural networks were trained, to predict financial performance. The classification accuracy rate of multilayer perceptron was also reasonably good. The results also showed that MLP of ANN is the most powerful predictors of financial soundness. Although future work will need to validate these findings in larger and more diverse samples, there is strong evidence that the proposed model can be used effectively to predict overall financial performance of business organizations in general and steel manufacturing organizations in particular and to help the management to design interventions that increase the overall financial performance.

REFERENCES

1. *G. Aslani, S. H. Momeni-Masuleh, A. Malek and F. Ghorbani (2009), Bank Efficiency Evaluation using a Neural network-DEA method, Iranian Journal of Mathematical Sciences and Informatics, Vol. 4, No. 2, pp. 33-48*
2. *Qeethara Kadhim Al-Shayea and Ghaleb Awad El-Refae (2011), Evaluation of Banks Insolvency Using Artificial Neural Networks, Recent Researches in Artificial Intelligence and Database Management, pp.113-118*
3. *Noraina Mazuin Sapuan, Suzaida Bakar, Hamidah Ramlan (2017). Predicting The Performance And Survival Of Islamic Banks In Malaysia To Achieve Growth Sustainability, SHS Web of Conferences, Vol. 36, No.16, pp.1-11*
4. *Mohamed M. Mostafa (2009), Modeling the efficiency of top Arab banks: A DEA–neural network approach, Expert Systems with Applications, Vol. 36, pp. 309–320*
5. *Peter Wanke, M.D. Abul Kalam Azad and C.P. Barros (2016), Predicting efficiency in Malaysian Islamic banks: A two-stage TOPSIS and neural networks approach, Research in International Business and Finance, Vol.36, pp. 485–498*
6. *Elsa Shokrollahpour, Farhad Hosseinzadeh Lotfi and Mostafa Zandieh(2016), An integrated data envelopment analysis–artificial neural network approach for benchmarking of bank branches, journal of Industrial Engineering International, Vol. 12, pp.137–143*
7. *Hsiang-Hsi Liu1, Tser-Yieth Chen1, Yung-Ho Chiu2, Fu-Hsiang Kuo (2013), A Comparison of Three-Stage DEA and Artificial Neural Network on the Operational Efficiency of Semi-Conductor Firms in Taiwan, Modern Economy, Vol. 4, pp. 20-31*
8. *Krzysztof Piasecki and Aleksandra Wójcicka-Wójtowicz (2017), Capacity Of Neural Networks And Discriminant Analysis In Classifying Potential Debtors, Folia Oeconomica Stetinensia, pp.129-142, DOI: 10.1515/foli-2017-0023*
9. *Nor Mazlina Abu Bakar and Izah Mohd Tahir (2009), Applying Multiple Linear Regression and Neural Network to Predict Bank Performance, International Business Research, Vol.2, No.4, pp.176-183*
10. *Ayan Mukhopadhyay1, Suman Tiwari2, Ankit Narsaria3and Bhaskar Roy Karmaker (2012), A New Approach to Predicting Bankruptcy: Combining DEA and Multi-Layer Perceptron, IJCSI International Journal of Computer Science Issues, Vol. 9, No.2, pp.71-78*
11. *Olanrewaju A Oludolapo, Adisa A Jimoh and Pule A Kholopane (2012), Comparing performance of MLP and RBF neural network models for predicting South Africa's energy consumption, Journal of Energy in Southern Africa, Vol. 23, No.3, pp.40-46*

12. *Mehdi Alinezhad Sarokolaei+, Parisa Alinezhad and Mohsen Akbari Khosroshahi (2012), A Comparative Study of Iranian Banks' Efficiency by Using Artificial Neural Networks and Multi-Linear Regression, 2nd International Conference on Management and Artificial Intelligence, Singapore, Vol.35,pp.80-83*
13. *Viju Raghupathi and Wullianallur Raghupathi (2015), Neural Network Analysis of Treatment Quality and Efficiency of Hospitals, Journal of Health & Medical Informatics, Vol.6, No.6,pp.1-12*
14. *Mahmoud H. Al-Osaimy (1998), A Neural Networks System for Predicting Islamic Banks Performance, Journal of King Abdul Aziz University: Econ. & Adm., Vol. 11, pp. 33-46*
15. *Birău, F. R. (2014). Forecasting financial time series based on Artificial Neural Networks. IMPACT: International Journal of Research in Business Management (IMPACT: IJRBM), ISSN (E).*
16. *Satish Sharma and Mikhail Shebalkov (2013), Application of Neural Network and Simulation Modeling to Evaluate Russian Banks' Performance, Journal of Applied Finance & Banking, Vol. 3, No. 5, pp. 19-37*
17. *Faruk Erinci and Serhat Duranay (2016), Predicting the Performance of Turkish Commercial Banks with Artificial Neural Networks, Recent Research in Interdisciplinary Sciences, Chapter 46, pp. 603-618, 2016*